Artificial intelligence in the detection of Radio Galaxies.

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Abstract

The article deals with artificial intelligence and machine learning, applying two reference automatic learning algorithms: the decision tree and the backward propagation neural network implemented in 30% of the Galaxy data set to observe and analyze the classification performance of machine learning techniques. A sample of radio sources with a radio brightness of

1.4 GHz, S1.4> 10mJy, which employs a new technique more efficient than previous methods, such as a pronounced spectral index or a small angular size, using near-infrared data to filter at low, they use radiogalaxies with redshift (z <2) by including only sources with a very weak identification or no detection in the K band or 3.6 μm.

INTRODUCTION.

Active Galactic Nuclei (AGN) are among the most luminous and energetic objects in the universe. Carl Seyfert [11] was the first to describe them as a class in 1943, but the physical processes occurring in these phenomena were first suggested by Woltjer [12], where it was noted the nuclei must be compact (~ 100 pc) and "extremely massive" (> 108 M⊙).

Many theories tried to explain the extreme power of the AGN [13], but the common explanation today is that AGN must be powered by accretion onto super massive black holes [14]. AGN emission covers all wavebands, from X-ray through the optical and radio, while powerful AGN are very luminous and can be found at the highest redshifts. Another property of AGN is the high variability of their emission observed at all frequencies on short time scales, which can be explained by a very compact structure of the emission region.

DEVELOPMENT.

Radio galaxies.

Radio galaxies are radio loud AGN with luminosities up to 1039 W, they derive their energy from gravitational potential energy on galactic scales due to their central super massive black hole and their radio emission is due to the synchrotron emission. Their main

observed structural components are radio core, radio jets, radio lobes and hotspots. The radio core is located in the center of the host galaxy and associated with the nucleus. This component usually has a flat spectrum and a linear size of less than ~ 0.2 pc. Radio jets link the core to the outermost part of the radio structure and may be visible over all their path or just part of it. They are collimated by the magnetic fields and constitute a small part of the total radio flux density of the radio galaxy. Their spectral index is usually between

$-0.8 < \alpha < -0.5$, where we define $S\nu \propto \nu\alpha$.

The lobes are double symmetrical structures located on either side of the nucleus and describe the extended region of radio emitting plasma. They also have steep radio spectra similar to the jets. Hotspots are bright components on the outermost part of the radio lobes with a linear size of ≤1 kpc. When the jet interacts with the intergalactic medium it can create a shock which converts part of the kinetic energy to relativistic particles which then emerge as hotspots.

A brief history of the Universe and the Epoch of Reionization.

The formation of the first galaxies played a crucial role in the evolution of structure in the universe but they also transformed the neutral intergalactic medium to ionised plasma, this period in the Universe is called the Epoch of Reionization. At redshift 1100 (~ 350,000 years after the Big Bang) the density of the Universe has decreased and cooled enough to allow photons to decouple from baryons and make the universe transparent, and it is at this point that we are able to see the first radiation permeating throughout the Universe in the form of the cosmic microwave background (CMB) radiation. After this time, the universe entered the dark ages, where the first stars and galaxies had yet to form and there was essentially no source of high-energy photons in the Universe. After about 400 million years the first galaxies began to form and start to emit radiation [15]. This period marks the start of the Epoch of Reionization (EoR). At the beginning of the EoR, the intergalactic medium was predominantly neutral except the regions close to the first objects. After enough UV- radiation has been emitted from these first objects the temperature and ionised fraction of the gas increases until the neutral gas is reduced to a small fraction of the density of the Universe, allowing photons to traverse through the Universe without being absorbed by the neutral gas.

Some of the key aims of current and future facilities are to determine which sources are responsible for reionising the Universe, how quickly this occurred, and when it ended. To measure the speed at which reionization occurs, one needs to trace the evolution in the abundance of neutral hydrogen at these early epochs.

The first direct measurement that established that we are beginning to see the EoR at $z > 6$ came from observations of the highest-redshift quasars found by the SDSS [16-18]. They found evidence for a Gunn-Peterson trough [19], i.e. the complete absorption of Lyα photons resulting in a trough of zero flux shortward of the Lyα emission line in the high-redshift

quasars due to a high neutral fraction. From these observations it is now clear that the EoR was coming to an end around z ~ 6.3.

However, the Gunn-Peterson trough does not provide the complete picture. This is because neutral hydrogen is too good at absorbing Lyα photons, therefore information about the rate of evolution of the neutral fraction within the EoR is difficult to determine and relies on assumptions about the intrinsic line profile of the Lyα emission line in distant quasars [20].

An alternative method of tracing the neutral hydrogen abundance at these early epochs is to use the hyperfine transition of neutral hydrogen at a rest-frame wavelength of 21 cm, i.e. in the radio waveband. At z > 6 this line is redshifted to low frequencies (ν < 200 MHz). It is only now becoming possible to observe these frequencies to sufficient depth where we may detect the signature of reionization through the 21 cm line with the imminent commissioning of the Low-Frequency Array and the Murchison Widefield Array [21], both of which lead towards the much larger Square Kilometre Array (SKA;[22]).

The evolution of neutral hydrogen within the EoR can be investigated broadly by two methods. The first utilizes the power spectrum variations in the intensity of the 21 cm radiation [24] and is where the majority of current work is concentrated. However, an alternative method would be to measure the 21 cm forest against background powerful radio sources [23], in much the same way that the Lyman-α forest is used to probe the intergalactic medium at lower redshifts. The key missing ingredient for this method to be successful is the discovery of powerful radio sources at sufficiently high redshift with which to observe the 21 cm forest.

High redshift radio galaxies.

High-redshift radio galaxies are powerful radio sources and hold the promise of being the ideal source with which to probe the evolution of Hi within the EoR. There have been many surveys which have tried to find high redshift radio galaxies [26-27-28-29-30], with the highest radio galaxy found thus far has a redshift of z = 5.19.

The problem that has hindered the discovery of more radio sources at the highest redshifts is not the paucity of deep radio data, but the difficulty of obtaining targeted follow-up spectroscopy of the many candidate sources within a given radio survey. This is due to the fact that powerful radio sources at z

> 5 radio sources make up << 1% of the total radio source population [35] in current large area radio

surveys such as the Faint Images of the Radio Sky at Twenty-centimetres (FIRST;[36]). To overcome this problem, previous studies have applied filtering criteria to eliminate lower redshift radio sources on the basis of their spectral index and/or angular size [26-28]. Indeed, this he selection of Ultra- Steep Spectrum radio sources resulted in the discovery of the highest redshift radio galaxy. However, it is clear that such methods are not 100 per cent efficient and a large number of radio sources at z > 5 may also be filtered out. This is crucially

important when the space density of the z > 5 radio source population is extremely low to start with.

Unlike QSOs, where the stellar emission is outshone by the emission from the accretion disk around the central supermassive black hole, radio galaxies also offer the opportunity to study the stellar populations of the most massive galaxies at the highest redshifts. Many studies have shown that powerful radio sources are Universally hosted by the most massive galaxies in the Universe at the epoch which they are observed [39-40], with many authors suggesting that they evolve into the brightest cluster galaxies in the low-redshift Universe [41-42]. Thus finding and studying the highest redshift radio sources not only enables the possibility of tracing the evolution of neutral hydrogen within the EoR but also allows us to investigate the speed at which the most massive galaxies form and the role of the central supermassive black hole in regulating the evolution of the host galaxy via AGN-driven feedback [43-44].

High redshift radio galaxies as probes of the EoR.

High redshift (z > 2) radio galaxies are a small subset of all radio sources. For the powerful nearby radio galaxy Cygnus A, at higher frequency the spectrum is steeper. If we assume that all powerful radio galaxies exhibit similar spectra, due to synchrotron or inverse Compton losses, we will see the steeper part of the spectra as the redshift increases. van Breugel & McCarthy (1990) showed that in the 3CR sample the spectral index and redshift (α − z) correlation leads support to such a hypothesis.

Other surveys have also shown that radio sources with ultra-steep spectral index α > 1 tend to be fainter and reside at higher redshift than the less steep spectral-index radio sources [26-34].

One physical interpretation of the α − z correlation is basically the relation between the band shifting and redshift, i.e. by increasing the redshift we could see the steeper part of the spectra. However, there is evidence that the spectra of at least some high-redshift radio sources are not curved, thus resulting in an absence of a steeper spectrum at high frequencies [45]. Another interpretation for the steeper radio spectra is needed and this could be that the high redshift radio galaxies reside in dense environments, as this is observed at low redshift. Since radio emission is more pressure confined in higher gas density environments, as a consequence radio lobe in rich galaxy clusters will expand adiabatically and lose energy via synchrotron and inverse Compton losses, resulting in a steeper radio spectra.

It is clear that methods such as steep-spectral index and angular size filtering are not 100 per cent efficient and a large number of radio sources at z > 5 may also be filtered out [34-39]. This is crucially important when the space density of the z > 5 radio source population is extremely low to start with

High redshift radio galaxy hosts.

These luminous radio galaxies have accreting super massive black holes, which emit at UV, optical, and soft X-ray energies but the bulk of the UV and optical emission is absorbed by dust, and allowing us a clear view of the host galaxy.

We have mentioned that the near infrared luminosity of high redshift radio galaxies makes them some of the most massive galaxies in the early universe, and the clumpy morphology of high redshift radio galaxies hosts is consistent with mergers and hierarchical models of galaxy evolution [46]. These distant sources may also be the progenitors of the most massive galaxies, brightest cluster galaxies and cD galaxies [41].

studies of high redshift radio galaxies have shown a tight correlation in the Hubble K -z diagram for powerful radio sources [39-47].

$K(z) = 17.37 + 4.53 \log10\ z - 0.31(\log10\ z)2.$

The Radio Surveys.

Although near-infrared surveys reaching sufficient depth to eliminate low-redshift $z < 2$ radio galaxies now exist, appropriate radio data is still also required. However, different populations dominate radio surveys at difference flux-density limits and it is clear that in order to find high-redshift radio sources, in particular those that reside within the epoch of reioinisation.

Faint images of the Radio Sky at twenty centimeters.

The Faint Images of the Radio Sky at Twenty Centimeters (FIRST) radio survey started in 1993 to produce the centimetre-wavelength equivalent of the Palomar observatory sky survey, which covers 10000 deg2 of the sky. The observations were made in the B-configuration of the VLA and the data calibrated using the AIPS data reduction package which provides the angular resolution of 5′′ and $\sigma RMS \sim 0.13$ mJy. The FIRST catalogue is a good option for matching with optical surveys while the radio structures down to 5′′ are resolved. In the catalogue, both peak and integrated flux density measurements are provided. They were measured by fitting a two-dimensional Gaussian to each intensity peak. The scientific properties of the FIRST survey are the following: good positional accuracy to have a large number of optical identification, the sensitivity to detect the radio sources below the break in the radio source counts ($\log N - \log S$) curve and angular resolution high enough to provide morphological classification of the sources.

Machine Learning Techniques; Models and Applications.

More than three decades, researchers and scientists have been emerging new techniques and methods on artificial intelligence in order to outperform the tasks that human beings are not capable. These tasks can be any problem from our daily lives. Even in last two decades, machine learning techniques with capabilities for classification, optimisation, and as well as prediction are developed for using to solve these problems. Many different and

challenging frameworks and models are proposed and available in the literature, and many interesting deployments have been increased in different fields such as physics, chemistry, computer communication networks, healthcare, and many more [1-2].

In this section, two machine learning algorithms; Back-propagation neural networks, and Decision Trees, which are considered in this research will be introduced, and discussed.

Back-propagation Neural Networks (BPNN).

Back-propagation neural network (BPNN) is the most common used and preferred artificial intelligence algorithm that is known as a supervised learning algorithm. In BPNN, it propagates back the error signal to update the weight during error minimisation. As mentioned, BPNN is popular because of its simplicity in implementation and efficiency in classification and prediction problems [1, 10–12, 21].

During the training phase of BPNN, error is calculated in output layer by comparing actual and target output and weights are updating according to the Equation 1.

$$w_j^{k+1} = w_j^k + lr\left(y_i - \hat{y}_i^k\right)x_{i,j} \quad (1)$$

where w_j^{k+1} and w_j^k are updated and old weights respectively, lr is learning rate parameter, and are actual and target outputs respectively, and is the input instance. y_i $\hat{y}_i^k$ $x_{i,j}$

Figure 1 shows general architecture of 3-layered BPNN.

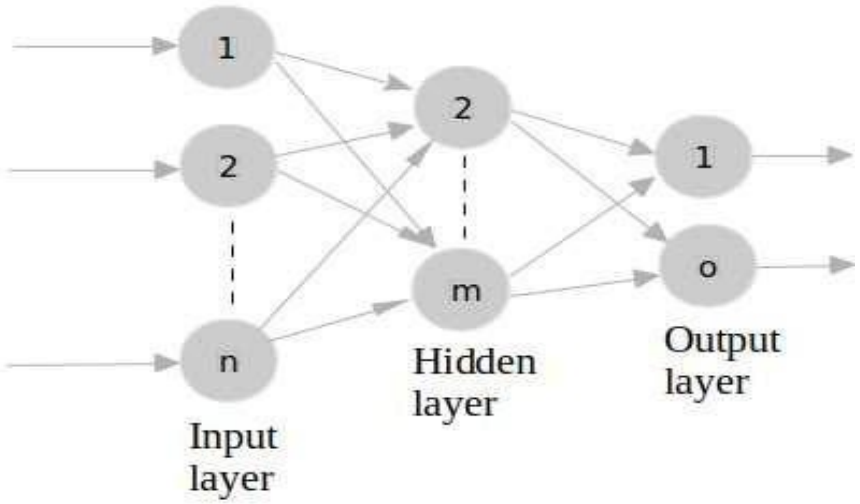

Fig. 1: General n-m-o architecture of BPNN.

Decision Tree (DT).

Another artificial intelligence method is decision trees (DT). DTs are tree-structured algorithms with initial root node, leaf nodes and decision nodes. In DTs, for classifying data, divide-and-conquer strategy is used until final leaf. Rules are assigned to each leaf and according to these rules, data flows until classified and decision trees have been used successfully in variety of classification problems recently [17–19].

For performing supervised classification, DT is a simple classifier in the form of a hierarchical tree structure. It comprises a directed branching structure with a series of questions. Simplicity and the speed are the main advantages of decision trees however, determination of initial root or the sequence of leaf nodes is the main drawback of decision trees. Figure 2 presents an example of a DT.

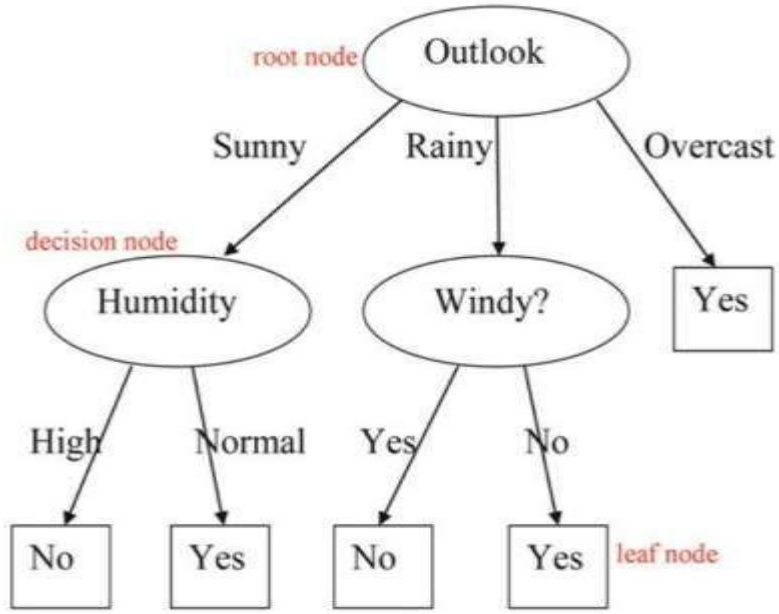

Fig. 2. Example decision tree.

Results and Discussions.

In this section, obtained results, discussions and comparisons will be presented. As stated earlier, the aim of this paper is to find the ideal classification algorithm considering achievement of optimal performance on Galaxy dataset. Thirty percent (30%) of instances of The Galaxy Dataset were considered that causes 30 patterns of total instances.

100 neurons were used in hidden layer of back-propagation neural network and Sigmoid activation function was used for hidden and output layers. 1000 epochs were used as stopping criteria of training for 70% training ratios.

For the experimental analysis, Decision Tree achieved 40% of classification ratio whereas Back Propagation Neural Networks achieved 73% classification ratio.

Table 1 shows all results obtained in this research and Figure 3 & 4 shows accuracy graphs for Back Propagation Neural Networks and Decision Tree Learning Algorithms respectively.

Table 1. Accuracy results for all methods.

Method	Accuracy
Decision Tree	40 %
Back-propagation NN	73 %

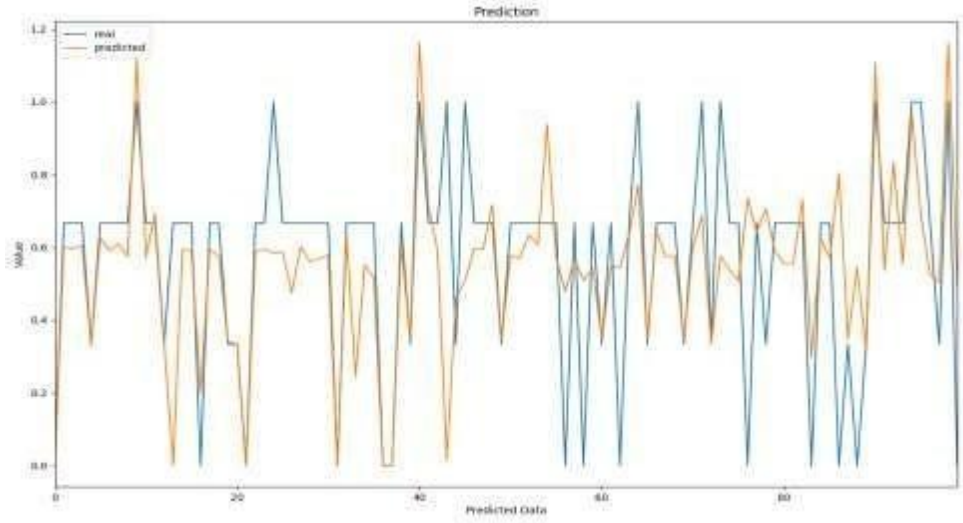

Fig. 3. BPNN Classification Graph.

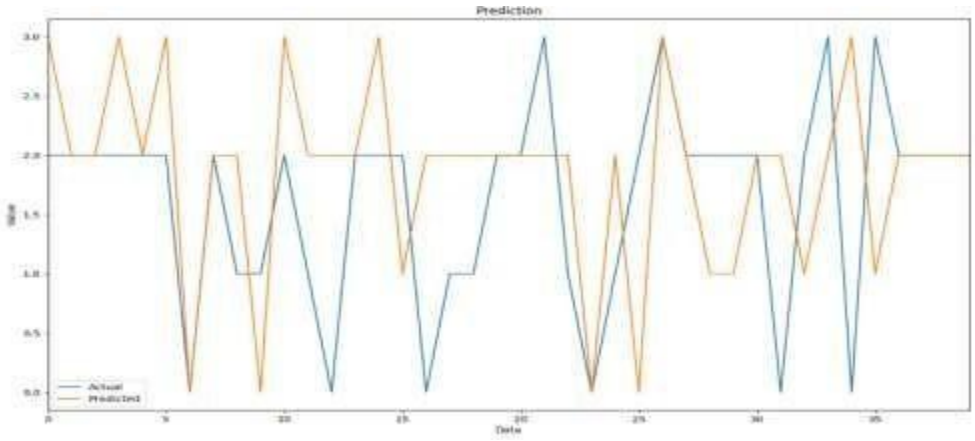

Fig. 4. DT Classification Graph

Considering above obtained results, Back-propagation neural network produced higher classification ratio with more steady results.

It is a general opinion in machine learning that the increment of training patterns or instances causes the increment of accuracy rates in classification results however, obtained results showed that either the efficiency of machine learning algorithms or the increment of the accuracy rates depend on the characteristics of dataset. In many two-class applications, Back-propagation Neural Networks produced superior results than Decision Trees in different studies. As it is mentioned above, those studies were performed for classification by different machine learning algorithms. These studies include different types of supervised or unsupervised neural network systems [2–3].

CONCLUSIONS.

Rapid developing of science and new technologies over the past decades have effected all aspects of human's life and so education. Dealing with extremely big data sets make teachers to apply computer science and artificial intelligence as part of their educational methods. Astronomy and astrophysics data sets evolution are among the fastest ones in science, thus the students are not training with traditional methods anymore.

In this paper, two benchmark machine learning algorithms; decision tree, and back-propagation neural network are implemented to 30% of The Galaxy Dataset in order to observe and analyze the classification performance of considered machine learning techniques. Obtained results show that machine learning techniques can efficiently classify the changes within the dataset and it can be concluded that the features of The Galaxy Dataset are linearly separable and do not need more complicated learning algorithms such as deep learning that increases computational time.

It is also obvious that more experiments with different parameters of considered machine learning techniques may increase accuracy rates. Future work will include the implementation of other machine learning algorithms such as Radial Basis Function Neural Network, Logistic Regression, and Random Forest by considering more data and make comparison between the learning methods as well as training ratio.

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